Use of a SPAR-H Bayesian Network for predicting Human Error Probabilities with missing observations

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Abstract: As [1] and [2] have discussed, many of the Performance Shaping Factors (PSFs) used in Human Reliability Analysis (HRA) methods are not directly measurable or observable. Methods like SPAR-H require the analyst to assign values for all of the PSFs, regardless of the PSF observability; this introduces subjectivity into the human error probability (HEP) calculation. One method to reduce the subjectivity of HRA estimates is to formally incorporate information about the probability of the PSFs into the methodology for calculating the HEP. This can be accomplished by encoding prior information in a Bayesian Network (BN) and updating the network using available observations.

We translated an existing HRA methodology, SPAR-H, into a Bayesian Network to demonstrate the usefulness of the BN framework. We focus on the ability to incorporate prior information about PSF probabilities into the HRA process. This paper discusses how we produced the model by combining information from two sources, and how the BN model can be used to estimate HEPs despite missing observations. Use of the prior information allows HRA analysts to use partial information to estimate HEPs, and to rely on the prior information (from data or cognitive literature) when they are unable to gather information about the state of a particular PSF. The SPAR-H BN model is a starting point for future research activities to create a more robust HRA BN model using data from multiple sources.

Keywords: Bayesian Networks, Human Reliability Analysis (HRA), human error probability, uncertainty

1. INTRODUCTION

In the nuclear power industry, Probabilistic Risk Assessment (PRA) models capture the sequences of events that can lead to core damage. These sequences typically include human failure events (HFEs), wherein human errors can result in the failure of a system or plant function. Human Reliability Analysis (HRA) is used to estimate the human error probability (HEP) for the HFEs in PRAs.

In many HRA methods, the HEP is the conditional probability of an HFE, given the performance context, $P(HFE|context)$. The context is represented by a set of Performance Shaping Factors (PSFs) or Performance Influencing Factors (PIFs), which are discretized into levels or states. HRA methods such as SPAR-H [3] are designed to assess $P(HFE|context)$, for a known context. In the SPAR-H methodology, the analyst determines the underlying context by selecting one level for each PSF. However, it is not always possible for an HRA analyst to gather perfect information on the level of all of the PSFs.

As [1] and [2] have discussed, many of the PSFs are not directly measurable or observable. Requiring the analyst to assign PSF levels for unobservable PSFs results in a great deal of subjectivity HRA. One method to reduce the subjectivity of HRA estimates is to formally incorporate information about the probability of the PSF levels into the methodology for calculating the HEP. This can be accomplished by encoding prior information in a Bayesian Network (BN) and updating the network using available observations.

Bayesian Networks have a number of benefits that enhance PRA [4], and these benefits extend naturally to HRA. In this paper, we focus on their ability to incorporate prior information about the probability of the PSF levels into HEP calculations. Recently, Bayesian Networks were introduced to the HRA field via two approaches: data-informed models [5, 6] and expert-informed models [7]. Both models are the result of research activities and therefore require further refinement and validation before they can be used for regulatory purposes. However, current HRA methods can be used to help construct BNs; this allows the HRA industry to exploit the benefits of BNs with minimal additional validation.

We combined an existing HRA methodology, SPAR-H [3], with expert-estimated probabilities for the PSF multipliers from US NRC documents [8] to build a SPAR-H BN. In this paper, we use the SPAR-H BN model to demonstrate how analysts can calculate HEPs for situations with perfect information and for situations with missing information. Use of perfect information produces results identical to the SPAR-H methodology. For situations when the analyst is unable to gather information about the level of a PSF, the prior information encoded in the BN is used to replace the analyst's lack of knowledge.

2. SPAR-H METHOD OVERVIEW

The Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) [3] method was developed to estimate HEPs for use in the SPAR PRA models used in commercial nuclear power plants. SPAR-H is used as part of PRA in over 70 US nuclear power plants and by the event assessment programs at the US NRC. SPAR-H also is the main model behind the Human Event Reliability Analysis (HERA) HRA database sponsored by Nuclear Regulatory Commission.

SPAR-H is used to quantify HEPs through the following steps:

1. **Determine the plant operation state and type of activity**. The SPAR-H method considers two plant states (at-power and low power/shutdown) and two types of activities (diagnosis and action). The two types of activities use the same equations and PSFs, but different PSF multipliers. In this paper, we present the model for action tasks during at-power operations.
2. **Evaluate PSF levels to determine the multipliers**. Assign a level for each PSF on the HEP worksheet. The SPAR-H method uses eight PSFs to represent the context. Each PSF level is associated with an HEP multiplier value. Table 2 contains the SPAR-H PSFs and the PSF multiplier values for action tasks[1].
3. **Calculate HEP using equation provided in the worksheets**. Two equations are provided; the equation depends on the number of negative PSFs (any PSF where the assigned level has a multiplier greater than 1). Equation 1 is used to calculate the HEP for situations with fewer than 3 negative PSFs. Equation 2 is used if there are 3 or more negative PSFs.

$$HEP = NHEP \cdot \prod_{1}^{8} S_i \tag{1}$$

$$HEP = \frac{NHEP \cdot \prod_1^8 S_i}{NHEP \cdot (\prod_1^8 S_i - 1) + 1} \tag{2}$$

where S_i is the multiplier associated with the assigned level of PSF i. For diagnosis tasks $NHEP = 0.01$ and for action tasks $NHEP = 0.001$.

3. BN OVERVIEW

A Bayesian Networks a type of quantitative causal model, which expresses the joint probability distribution, P, of a set of variables in terms of the conditional probability distributions. The graphical

[1] Note that the SPAR-H method also has an "Insufficient Information" level for each PSF, with a corresponding multiplier of 1. This is not included in Table 2. See Section 6 for more information.

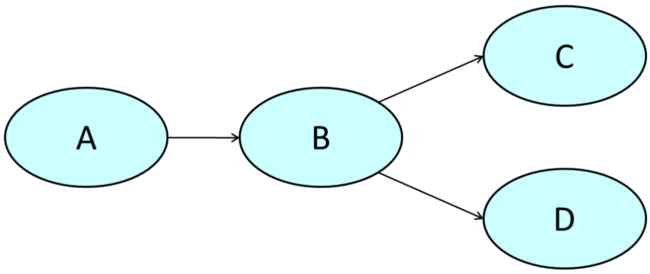

Figure 1: Example Bayesian Network diagram for four nodes, displaying the conditional dependence and independence relationships among nodes A, B, C and D.

part of a BN consists of nodes N (the variables or PIFs) and directed arcs, which specify conditional dependencies between nodes). Most BNs use discrete conditional probability tables to express the strength of the relationships between the variables.

A BN is a knowledge base that can be used to reason about events, based on the set of information that is currently available. From a Bayesian statistical point of view, this BN is the prior probability distribution for the system. Bayesian updating is used to make inferences (update the state of knowledge in the network) as additional information (e.g., analyst observations) become available. Since the BN includes prior information about all of the nodes in the network, analysts are not required to make observations about variables that are not readily observable; the prior information about each node is used in places where the analyst lacks new information.

3.1. BN Structure

The BN structure encodes two types of information: the variables of interest (nodes) and the causal dependencies among the variables (arcs). Each node in a BN has a finite number of mutually exclusive states. The BN structure displays the conditional dependence and independence relationships among entire universe of variables. Figure 1 can be used to illustrate this concept. Directed arcs are used to indicate causal relationships between nodes, with the arrow head indicating the direction of causality. Node A directly influences node B. Node B directly influences both C and D. There is no direct arc between A and C, rather, A indirectly influences C through B. If B is known, A and C are independent (therefore, they are conditionally independent, given knowledge of B). All root nodes are conditionally independent, and all other nodes are conditionally dependent only on their direct parent nodes.

The BN structure can be built using expert opinion, system dependency information, available data, literature or any combination of sources. Pearl [9] provides guidance to help identify causal relationships to be encoded in the BN, and Lu & Druzdzel [10] describe software that aids in the process of building graphical models based on causal mechanisms.

3.2. BN Quantification

Once the BN structure is complete, each node is assigned a probability distribution, usually by populating discrete conditional probability tables (CPTs). The CPTs contain all known information concerning the probabilities of the nodes and the probabilistic relationships between nodes. The conditional probability table will contain one probability value for each possible configuration of states of the node and its parents.

The size of the CPT depends on the number of parents. Many BNs use binary nodes to reduce the complexity of the CPTs. For a binary node with n binary parents, the CPT will contain $2^{(n+1)}$ cells. The nodes in Figure 1 are all binary. Since A has no parents, it is fully specified by $P(A = a)$ and

$P(A = \overline{a})$, which must sum to 1.0 according to the laws of probability. The conditional probability table for node b is displayed in Table 1. The conditional probability tables for c, d will be similar to Table 1. Note that in the CPTs, each column must sum to 1.0 (i.e., the probability must sum to 1.0 for each state of the parent).

	Parent	$Pr(a)$	$Pr(\overline{a})$
Child	$Pr(b)$	$Pr(b \mid a)$	$Pr(b \mid \overline{a})$
	$Pr(\overline{b})$	$Pr(\overline{b} \mid a)$	$Pr(\overline{b} \mid \overline{a})$

Table 1: Conditional probability table for node b with one parent, a.

The probabilities can be assigned using expert opinion, available data, deterministic relationships, or any combination of information. Conditional probabilities can be populated by using expert opinion, data, or a combination of both. The reader is referred to the references for additional information about conditional probability in Bayesian networks [9, 11, 12].

Once a CPT is assigned to each node, the BN calculates the unconditional (marginal) probability distribution for every node, N, from the conditional probability table for N and the probability of the parents (via the law of total probability, Equation 3).

$$P(N) = P(N|parents) * P(parents) \tag{3}$$

3.3. Reasoning with a BN

Once the initial BN is complete, an HRA analyst would use this model to make inferences about problems (reasoning) via Bayesian updating. The initial BN represents the *prior* joint probability distribution of the system. To use the BN, the analyst makes observations (sets evidence) about certain nodes. By setting evidence, an analyst is providing the model with new information (e.g., recently collected data, observation of a particular state of a PSF) about the state of the system. This information is automatically propagated through the network to produce *posterior* joint probability distribution of the model. These updated probabilities are the result of both prior information in the BN and the new evidence. This process can be repeated every time new evidence becomes available.

4. SPAR-H BN MODEL

To demonstrate the usefulness of the BN methodology for HRA, we built a BN based on the SPAR-H methodology. The Bayesian Network was constructed using Hugin software version 7.5. We used two sources of information to construct the BN based on the SPAR-H methodology. The SPAR-H methodology [3] was used to build the BN structure and the conditional probability table for the Error node. NUREG/CR-6949 [8] provides expert estimates of the probability of the PSF levels; this information was used to assign the marginal probability tables for the PSFs. The target of the HRA analysis is the marginal probability of the Error node. The Bayesian Network uses Equation 3 to get the marginal probability of Error from the conditional probabilities in the model.

4.1. Graphical Structure

There are 9 nodes in the graphical model: one node for each of the 8 PSFs, and one node for a human failure event ("Error"). Each PSF nodes has the same levels that the PSF has in the SPAR-H method (excluding the level "Insufficient Information"); these are listed in Table 2. The Error node is discrete and has two states: error occurs ($P(Error)$) and no error occurs ($1 - P(Error)$).

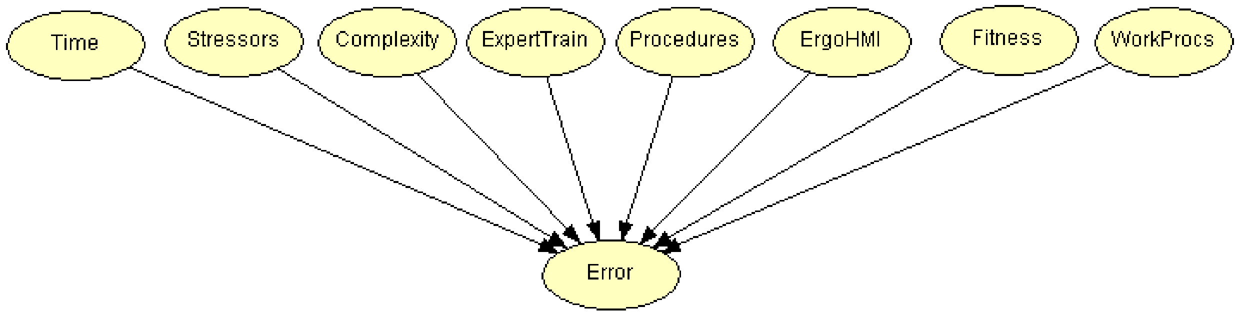

Figure 2: Naive BN representing the conditional independence statements in the SPAR-H method.

The graphical structure of a BN encodes the conditional dependence statements about the variables in the model. According to the SPAR-H manual, each of the 8 PSFs directly impacts the probability of error, so a causal arc goes from each PSF node to the Error node. The SPAR-H method treats each of the 8 PSFs as independent of the other PSFs, so causal arcs were omitted between all of the PSFs[2]. The resultant Bayesian Network is pictured in Figure 2.

4.2. PSF Node Probabilities

In the BN in Figure 2, the 8 PSFs are root nodes. The marginal probability tables for the PSF nodes encode the probability of observing each PSF level during nuclear power plant operations. NUREG/CR-6949 provides estimated probabilities for the PSF multipliers in SPAR-H; these probabilities were developed using by limited knowledge of the shape of the PSF distribution and expert judgment [8]. In the SPAR-H BN, we use the NUREG/CR-6949 probabilities for all of the PSFs except for Experience/Training.

The NUREG/CR-6949 distribution for the Experience/Training PSF assigned equal probability ($P = 0.33$) to the three possible levels. Upon review of the SPAR-H method, it was determined that Low Experience/Training is assigned for operators who have less than 6 months of experience or training. It is unlikely that 33% of operating crews have Low Experience/Training, so we adjusted probability distribution for this PSF. We assumed that Experience/Training has a uniform distribution over a 20-year career-span. We assumed that Low corresponds to 0-6 months of experience, Nominal corresponds to 6 months to 10 years of experience and High Experience/Training corrsponds 10 to 20 years of experience.

The probability values for the PSF levels are presented in Table 2. In the original SPAR-H method, each PSF has an additional level: "Insufficient Information" (with a multiplier of 1.0). This has been omitted in the BN version of SPAR-H, because in the Bayesian framework, prior information is used in situations where there is missing information. In a BN it is not necessary to explicitly include an insufficient information state, because the prior information in Table 2 is used for inference when additional information is unavailable.

4.3. Conditional Probability of Human Error

The SPAR-H method provides a formula to assess the HEP based on the PSF levels selected by the analyst. This formula deterministically assigns $P(Error|context)$, where *context* represents the assigned PSF levels. To build the CPT for the error node, it is necessary to determine $P(Error|context)$ for every for every possible context (combination of PSF levels). For two PSF levels (*Available Time = Inadequate* and *Fitness for duty = Unfit*), the final HEP is assigned the value of 1.0 regardless

[2]The SPAR-H manual acknowledges that there is some dependence among the PSFs, however, the SPAR-H method treats the PSFs as independent entities. Future versions of the SPAR-H BN may include these dependencies.

Table 2: Prior probabilities for the PSF multipliers based on expert elicited values in NUREG/CR-6949 [8].

PSF	PSF Level	Multiplier	Probability
Available Time	Expansive time	0.01	0.023
	Extra time	0.1	0.136
	Nominal time	1	0.683
	Barely adequate time	10	0.159
	Inadequate time	HEP=1.0	1E-06
Stressors	Nominal	1	0.841
	High	2	0.136
	Extreme	5	0.023
Complexity	Nominal	1	0.500
	Moderately complex	2	0.341
	Highly complex	5	0.159
Experience/Training	High	0.5	0.500
	Nominal	1	0.475
	Low	3	0.025
Procedures	Nominal	1	0.450
	Available, but poor	5	0.300
	Incomplete	20	0.200
	Not available	50	0.050
Ergonomics/HMI	Good	0.5	0.159
	Nominal	1	0.683
	Poor	10	0.136
	Missing/Misleading	50	0.023
Fitness for duty	Nominal	1	0.841
	Degraded Fitness	5	0.159
	Unfit	HEP=1.0	1E-06
Work Processes	Good	0.5	0.159
	Nominal	1	0.819
	Poor	5	0.023

of the state of the other PSFs. For all combinations of PSFs that included one of these levels, $P(Error|context) = 1.0$.

Hugin includes a Table Generator Function that allows model builders to develop mathematical expressions for the CPT. In the remainder of the CPT, the conditional HEP was assigned by direct application of the appropriate SPAR-H formula. As discussed in Section 2, the SPAR-H method uses a correction factor if there are three or more PSFs in a negative state. In the Hugin model, we added a dummy node that counted the number of PSFs in the negative state. For cases where there were 3 or more negative PSFs, the modified SPAR-H formula was applied to determine the HEP. For the remaining cases, the original SPAR-H formula was used to inserted to calculate the conditional HEP. We then added a test to determine if the calculated HEP would exceed 1.0. In these cases, the conditional HEP was rounded down to 1.0.

4.4. HEP Calculation

The Bayesian Network uses Equation 3 to get the HEP (the marginal probability of error) from the conditional probabilities in the model. To determine the final HEP in the SPAR-H BN, the marginal probabilities for the PSFs are multiplied by the conditional probability table for human error. For the SPAR-H BN, this is:

$$P(Error) = P(Error|PSF_1, PSF_2, ...PSF_8) * P(PSF_1) * P(PSF_2) * ... * P(PSF_8) \tag{4}$$

The SPAR-H BN is the prior information about human error probability, based on the SPAR-H model

Table 3: Summary of the input and the results for the SPAR-H BN example cases. The numbers refer to the selected PSF multiplier. The ? symbol indicates no new information has been added to the BN for the PSF.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Available Time	1	1	1	1	1	?
Stressors	1	1	1	1	1	?
Complexity	1	1	1	1	1	?
Experience/Training	1	1	1	1	1	?
Procedures	1	1	1	1	1	?
ErgoHMI	1	10	?	See text	See text	?
Fitness for Duty	1	1	1	1	1	?
Work Processes	1	1	1	1	1	?
HEP	1.00E-03	1.00E-02	3.27E-03	5.50E-03	2.49E-03	0.0567

and the NUREG/CR-6949 data. This represents the baseline HEP, where there is no information from the HRA analyst. If there is information available from the HRA analyst, the analyst enters the available information (observations of PSF levels) by setting evidence in the BN software. Setting evidence on a variable updates the probability distribution that is used in Equation 4. If the analyst does not set evidence on a variable, the BN uses the prior probability distribution. As evidence is entered (or retracted), the BN software combines the prior model with the new information and automatically calculates the updated HEP.

5. RESULTS

The BN in Section 4 encapsulates the prior information about human error probability, based on the SPAR-H model and the NUREG/CR-6949 data. This represents the baseline model (where there is no information from the PRA analyst). In most HRA applications, the HRA analyst will have at least some information to add to the prior model. We ran several cases using different types of information: perfect information, partial information, or no new information. The test cases and results are described below and are summarized in Table 3.

5.1. Cases 1 and 2: Perfect Information

To set evidence for perfect knowledge of the level of a PSF, the analyst sets evidence that the probability of the known PSF level is 1.0 and all other PSF levels are 0. This type of evidence replaces the probability distribution in Table 2, so the analyst is not using any of the prior information. If the HRA practitioner has perfect knowledge of the level of all eight PSFs, the BN model produces results that are identical to applying the current SPAR-H formula.

Cases 1 and 2 display the input and the results for analysts with perfect information about the level of all of the PSFs. In Case 1, the analyst knows that all of the PSFs are in the “nominal” level. Setting all of the PSFs to be nominal in the BN produces an HEP of 1.0E-3, which equals the baseline HEP for action tasks in the SPAR-H formula. In Case 2, the analyst knows that the Ergonomics PSF is “Poor” and the remaining PSFs are nominal. The resulting HEP is 1.0E-2, which is identical to the HEP that the SPAR-H formula provides.

5.2. Cases 3, 4, and 5: Partial information

Ergonomics/HMI is one of the PSFs that is not directly observable according to Boring et al. [2]. In the original SPAR-H methodology, the analyst would have to select a level for Ergonomics, regardless of its observability. In this case, the analyst would select “Insufficient Information” which, in the

SPAR-H formula, is equivalent to setting the level to "Nominal." This produces an HEP of 1.0e-3, just like Case 1. This mathematically equates a *lack of information* about the Ergonomics to *perfect* information that Ergonomics are nominal. However, the absence of information about the ergonomics PSF does not mean that the ergonomics are nominal in reality.

A better way to address the lack of information about Ergonomics is to use the prior information in the BN, instead of making an observation about Ergonomics. Cases 3, 4, and 5 display the input and results for analysts with partial information. In all three cases, the analyst has perfect information about the level of all of the PSFs except for Ergonomics. In Case 3, the analyst has no new information about the level of Ergonomics PSF. In Cases 4 and 5 the analyst has some information about the Ergonomics PSF, but the information is not perfect. In both Case 4 and Case 5, the analyst believes that there is a 0% chance of Ergonomics being Missing/Misleading and a 0% chance of Ergonomics being Good.

In Case 4, the analyst also believes that a 50% probability that the Ergonomics level is Nominal and a 50% probability that the Ergonomics level is Poor. In Case 5, the analyst is unsure about the probability of being Nominal or Poor, so the analyst does not enter any additional information about Ergonomics. In this Case 5, the analyst has entered partial evidence about Ergonomics. The BN performs Bayesian updating: it combines the prior distribution with the new information. The BN uses Bayesian updating to get posterior probability on Nominal 0.834 and Poor to 0.166.

The resulting HEP for Case 3 is 3.27E-3. This is different than the probability in Case 1, because it uses the prior probability distribution for Ergonomics rather than perfect information about Ergonomics. The resulting HEPs for Case 4 and Case 5 represent scenarios where the has ruled out the Missing/Misleading and Good levels for Ergonomics. However, in Case 4 the analyst made an explicit statement of equal probability between Nominal and Poor. In Case 5, the analyst has made a statement of equal likelihood between Nominal and Poor. In Case 4 the analyst evidence has reduced the probability of the Nominal level and increased the probability of the Poor level. In Case 5, the analyst increased the probability of both levels. This results in Case 4 having higher posterior HEP (5.50E-03) than in Case 5 (2.49E-03).

5.3. Case 6: No new information

Case 6 represents the prior model for the system, without any additional input from an HRA practitioner. This is equivalent to assuming that all of the PSFs are at the "Insufficient Information." In the original SPAR-H method, the HEP multiplier for each of these conditions is 1, so the HEP would be (just like Case 1). However, the absence of information about a PSF does not mean that the PSF is nominal in reality. In a Bayesian framework, when a piece of information is unknown, analysts use prior information about the system/process to fill in the gaps. In the SPAR-H BN, the prior distributions from Table 2 are propagated through the model to produce a final HEP.

The SPAR-H BN, with the prior probabilities discussed above, provides a baseline HEP of 0.058 for action tasks. This is a substantial, important difference from the assumed baseline HEP of 1.0E-03, and this difference merits further exploration. It is possible that the baseline HEP in SPAR-H was intended to capture both the $P(Error|PSFs)$ and $P(PSFs)$, and it is possible that the expert elicited priors are conservative. Future research activities should be dedicated to validating the information from NUREG/CR-6949, validating the SPAR-H method, or both.

6. DISCUSSION AND NEXT STEPS

The model in this paper is a starting point for expanding the use of BNs within HRA. Using a BN framework for HRA provides a number of benefits to HRA practitioners. The original SPAR-H method requires analysts to make a definite statement about all 8 PSFs, but according to Boring [2], many

PSFs are not directly observable. Using a BN it allows HRA analysts to make inferences with missing observations and imperfect information. In the original SPAR-H method, analysts have the option of assigning the "Insufficient Information" level for a PSF, however, assigning "Insufficient Information" is mathematically equivalent to assigning the PSF to the "nominal" level. It is not justifiable to equate the lack of information with perfect information that the the PSF level is nominal. Using prior information eliminates this problem.

The BN in this paper was produced by synthesizing two types of information: the SPAR-H model and expert estimates from the NRC. There are additional data-collection activities occurring throughout the nuclear industry (e.g., CORE-DATA [13], OPERA [14], HERA [15]), and there is a huge body of psychological research that could be of predictive value for HRA. The BN framework can be used to synthesize data and information from multiple sources.

BNs formally display and document the assumptions and information that go into the model. This provides an opportunity for industry and researchers to verify the assumptions that may have been made during the modeling process. In this paper, it was assumed that the career of an NPP operator lasts 20 years, and that experience is uniformly distributed. This assumption about the distribution of experience could be verified and/or adjusted using plant-specific information. Additionally, the BN framework can easily incorporate changes to the method without requiring the entire HRA method to be rebuilt and validated. If one of the underlying assumptions changes, the BN can be locally modified. For example, the probabilities of the Experience/Training PSF can be adjusted without making changes to the remainder of the model. In contrast, expert-based models with implicit assumptions must be rebuilt when assumptions change.

The authors are currently working to integrate data from HERA and CORE-DATA into the SPAR-H BN. In the next version of the SPAR-H BN model, the event data will be used to populate the conditional probability tables for the PSFs. We will also use event data to modify the baseline HEP (1E-03) from the original SPAR-H method and we intend to include uncertainty about the value in the final BN.

By shifting to a BN structure, we are becoming more explicit about the information that goes into the model. The SPAR-H BN can be used as a starting point for future research activities. The difference between the baseline HEP in the original SPAR-H method and in the SPAR-H BN (Case 6) is an interesting starting point for research. Future research activities should be dedicated to validation of the prior probabilities on the PSFs from NUREG/CR-6949 and validation of the way the SPAR-H formulas were combined with the PSF priors.

It is critically important to explore methods for modifying the SPAR-H BN structure to better represent the interdependency among the PSFs. Groth and Mosleh [6] have proposed an interdependent structure based on analysis of HRA data. Cognitive models could be used to develop an expert-informed interdependency structure in explicit, traceable manner. The SPAR-H manual discusses cognitive models that were considered in the construction of the method, but these are included only implicitly in the SPAR-H calculation framework. Future research efforts should be dedicated to encoding these cognitive models explicitly in the BN.

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